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Operate, not Amputate: Rule 201 as an Example of a Surgical Approach to Dealing with Toxic Short Selling

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An early version of this paper was published as part of Oscar H. Florindo's thesis, Florindo (2021). We would like to thank comments from Yakov Amihud, James Angel, Eudald Canadell, Carole Comerton-Forde, Isabel Figuerola, Belen Nieto, Pedro Serrano and Gonzalo Rubio and Seminars at CNMV, Universidad Complutense and Wolpertinger 2024 conference. The short sale information from the NASDAQ and NYSE-ICE exchanges was provided as a courtesy by the exchanges. The research in this paper was financed by the Ayuda Fundación BBVA a Investigadores y Creadores Culturales (2015). It has also benefited from financial support from grants from the Agencia Estatal de Investigación (PID2019-104649RB-I00/AEI/10.13039/501100011033). We also thank the financial support from Comunidad de Madrid (Programa Excelencia para el Profesorado Universitario, convenio con Universidad Carlos III de Madrid, V Plan Regional de Investigación Científica e Innovación Tecnológica). The analysis and conclusions set forth are those of the authors and do not indicate concurrence by the financing institutions in any way.

ABSTRACT

In 2011 the SEC introduced Rule 201 aimed at striking a balance between limiting the threat of short sellers on price stability while interfering as little as possible with the provision of liquidity and the process of price discovery. In this paper we provide a novel evaluation of this Rule using over two years of intraday data, carefully matching restricted and control assets, and separating local effects around the implementation from those over the remainder of the trading day. We find that the Rule achieves its objectives: despite a 4% drop in volume, liquidity and volatility improve (the spreads fall by 7% and the range by 13%). Our analysis indicates that the restrictions achieve this by increasing the cost of short selling in a way that primarily affects toxic short sellers.
Keywords: Short sale bans, Rule 201, overpricing, price efficiency, price discovery

JEL Classification: G14, G18

1. Introduction

Short sale restrictions have a long history and are a significant point of contention in popular debates over stock market regulation, specially at times of generalized stock market price declines. The general consensus among regulators is that short selling is a necessary part of well-functioning markets but at times it can be a source of price instability. In the past, the most common regulatory approach can roughly be described as: allow short selling and intervene only at times where the risk of price instability is greatest, and do so by essentially forbidding short selling.[1] For a recent example consider Spain where short selling has been possible for a long time. However, on March 12th, 2020, when the Covid crisis started, the regulator introduced a temporary ban on all short sales for a large subset of shares traded in the Spanish stock market. The ban was introduced for a month initially, and it was later extended until May 18th, 2020.[2] Similar bans were also introduced in multiple countries in response to the 2008 financial crisis.

In contrast to Spain, in the U.S. no additional short sale restrictions were implemented in response to the pandemic, relying instead on the existing regulation introduced by the SEC during 2011. This, then novel, regulation, the Rule 201, established when, how, and how long to impose short sale restrictions, and is significantly different from other bans introduced in the past. In particular, this regulation differs in three key aspects: (i) it is triggered automatically by a market event (a price drop of 10% relative to the previous day's closing price), (ii) it lasts for a pre-defined and relatively short period of time (the rest of the trading day and the next 24 hours[3]), and (iii) it imposes short sale restrictions only on aggressive short sales, that is it forbids short sales at or below the best bid. In addition, it includes a list of conditions to exempt short sales that are deemed necessary for the

[1] In most cases such short selling bans include exceptions related to market-making and essential basic trading strategies, such as hedging and derivative trading.
[2] The ban applied to stocks that suffered a significant price drop on March 12th, 2020, which essentially covered the entire Spanish stock exchange. See Losada-Lopez and Martinez-Pastor (2020).
[3] If the price also suffers a 10% drop in the next 24 hours, the restrictions are extended another 24 hours.

well-functioning of the market–although such exemptions are not novel and have been commonly included in the past, when banning short sales.[4]

The current paper provides an in-depth analysis of the Rule 201 restrictions. We evaluate the effectiveness of these restrictions and conduct a broad study of the Rule's effects to identify the channel through which these restrictions operate. With this we aim to provide a deeper understanding of the effectiveness of the regulation and its potential value for other countries.[5]

What we find is that Rule 201 is effective in reducing selling pressure and slowing down price drops. We also find that it is accompanied by increased liquidity and reduced informed trading, specially from trades with very short-term or no informational advantages. Furthermore, these results are accompanied by changes in trading strategies that become more passive and/or re-rout orders to dark venues. This suggests that short sale regulation of this type is positive for the market.

In addition to the novelty in the breadth and scope of our analysis, we introduce a novel methodological approach by creating a pseudo-trigger event for the control group. This pseudo-trigger allows us to also include an analysis of the local circumstances surrounding the introduction of the regulations, and thereby extend our identification of the causal effects of the ban from the broad effects generated over the remainder of the day, to the local ones, in the minutes immediately surrounding the implementation of the restrictions. [6] We incorporate a placebo analysis that validates our approach and conclusions. Our analysis finds that the circumstances triggering the event (the 10% price drop) are significantly different from normal. However, these circumstances are not an effect of the regulation, as we observe the same results in both the control and placebo groups.

[4] See `https://www.sec.gov/rules/final/2010/34-61595-secg.htm`.

[5] EU Regulation No 236/2012 of the European Parliament and of the Council of 14 March 2012 allow similar rules in the EU but we have failed to find any country that implements them.

[6] The validity of our analysis is strengthened via an (initially unintended) replication dimension, as it repeats a previous analysis by the same authors on a smaller sample published as a working paper (Florindo et al., 2022). To ensure a disciplined replication approach we repeat all and only those analysis in Florindo et al. (2022) using the new expanded sample.

2. Related Literature and the Theory on Short-sale Restrictions

2.1 Related Literature

This paper contributes to our understanding of regulatory frameworks and empirical patterns related to short sale limitations in financial markets. The existing empirical research in this field primarily falls into two main categories: (i) The former US regulation on short sale restrictions (the uptick rule) and the associated short sale pilot program implemented to evaluate its effects (May 2, 2005 to August 6, 2007). (ii) The implementation and/or removal of nationwide bans on short sales, affecting either all stocks or a significant portion of traded stocks, in response to financial crises. This study contributes to a third category of literature, which examines the current US regulation, Rule 201, introduced in 2011 and still in effect today, and can be implemented in EU, as is included in EU Regulation No 236/2012.

While there is some variation in the findings, the majority of studies from the uptick rule and the associated short sale pilot suggest that the removal of the uptick rule had modest effects on market quality and short-selling activity, with potentially more pronounced impacts on smaller stocks (see, Alexander and Peterson (2008), Diether et al. (2009), Grullon et al. (2015) or Fang et al. (2016)). Following the conclusion of the pilot, effective July 3 2007, the restrictions on short sales imposed by the uptick rule were removed

The recent literature on the implementation and/or removal of nationwide bans on short sales focuses on the ones surrounding the 2008 financial crisis. In the United States, the SEC implemented emergency measures, including a prohibition on short sales of financial stocks, and similar measures were implemented in many countries. Research on these restrictions yielded mixed results. Boulton and Braga-Alves (2010) observed stock overpricing at the announcement of the ban, followed by a significant price decline upon its expiration. Boehmer et al. (2013) found no significant effect on asset prices but noted substantial market quality degradation. In a broader context, Beber and Pagano (2013) examined similar bans across 30 countries, concluding that while these restrictions did not affect price levels, they increased volatility and slowed price discovery. Marsh and Payne (2012) looked at the UK ban on short sales for financial stocks, and found that it led to a deterioration in liquidity and market quality. Overall, evidence suggests that short-sale bans generally resulted in poor market quality, decreased liquidity, and slower price discovery, while having limited or no positive impact on stock prices, except for the improvement in trade informativeness found in Kolasinski et al. (2013).

Rule 201 offers an alternative way to regulating short sales compared to the broad temporary bans imposed after the 2008 financial crisis. Recent research on the true effects of Rule 201 is scarce. We find five key papers in this area: Jain et al. (2012), Halmrast (2015), Davis et al. (2017), Switzer and Yue (2019), and Barardehi et al. (2024).

The earliest contributions, Jain et al. (2012) and Halmrast (2015), cover the period of the introduction of the Rule. Jain et al. (2012) analyze the period immediately surrounding the implementation of the Rule and include only two months after February 2011 (the compliance date). They are unable to document any clear benefits of the SEC Rule 201 after comparing assets-days with price drop of less than 10% with those with smaller price drops, as well as with those with price increases (separating the latter two groups). They conclude that the 201 restrictions would have been ineffective in reducing price declines. Halmrast (2015) also finds no significant effect of the ban on stock prices. The paper excludes part of 2012, precisely the most volatile months, which are the ones for which assessing the effects of the ban are most interesting for market participants and regulators. The latter two papers also do not go beyond 2012 in their analysis. Davis et al. (2017) focuses on price efficiency and conclude that it declines with the restrictions, as evidenced by an increase in price clustering, while Switzer and Yue (2019) document no effect on the main metrics of market quality. Overall these studies find evidence of a limited impact of the regulation.

In contrast, Barardehi et al. (2024) study the effectiveness of Rule 201 using intraday data from March 2011 to March 2013, and find the opposite effect, namely that the regulation is effective in reducing overall short-sale volume and reducing price declines, and that the effect on prices is not reversed after the removal of the restrictions. Our study looks at the broader effects of the activation of the regulation, and its effects on market quality. We confirm the effectiveness of the regulation on short-sale volume and prices, and, guided by the theoretical literature, we explore the possible channels through which the regulation takes effect. We find evidence that the effectiveness of the regulation is driven by its effect on traders with a negligible or very short-lived informational advantage. This effect is accompanied by a positive effect on market-making and volatility, and mixed results on price efficiency.

Our analysis also incorporates local effects surrounding the triggering event, as in Jain et al. (2012), but using a novel pseudo-trigger event in the control group, an approach we validate with a placebo analysis. This allows us to consider the possibility of magnet effects, which have been for other endogenously triggered rules, such as circuit breakers and volatility stops (Miller (1989), McMillan (1990), Madhavan (1992), Abad and Pascual (2007), Hsieh et al. (2009), and Hautsch and Horvath (2019)) but not for short sale restrictions. We find that there are significant and robust effects around the studied trigger events, but this effect is common for both the trigger and the pseudo-trigger events, and hence not related to the short sale restrictions.

2.2 Short Selling Theories

We use existing theoretical models of short selling behavior to guide our identification of the mechanism through which the Rule 201 restrictions operate. From the theoretical point of view, the literature identifies four types of motivations behind short selling, each of which generate slightly different predictions on the effect of a ban on short sales. First, we find the type of behavior that makes headlines at times of financial crisis and generates political pressure for short term bans like the ones observed after the 2008 crisis is short selling by toxic traders running bear-raids and predatory trading strategies, Brunnermeier and Oehmke (2013). A ban on short trading would limit the negative and value-irrelevant price pressure from these strategies, improving market conditions and reducing the frequency of large negative price drops. The second motivation is informational. Traders that have negative information about a stock and want to profit from this information want to sell the stock. If they do not own the stock, they will sell the stock short, if possible. In this case, a short sale ban would limit the incorporation of negative information on the underlying asset into the stock price. This then reduces price informativeness, price efficiency, and generates overpricing (Miller (1977), Diamond and Verrecchia (1987), Boehmer and Wu (2012)), and future large price drops (Hong and Stein, 2003). The third motivation is liquidity provision. Short selling bans limit the ability of market-makers to manage their inventories (Beber et al., 2020) and provide liquidity in option markets (Battalio and Schultz, 2011). A ban hinders this, reducing market liquidity. Finally, the fourth motivation is liquidity demand and the presence of differences of opinion. Pessimistic traders and those with a short-term liquidity need may use short selling as a way to obtain liquidity (Diamond and Verrecchia (1987); Boehme et al. (2006)). Banning these trades reduce the volume coming from the more pessimistic traders, increasing frictions and reducing liquidity.

Because the Rule 201 ban is not an outright ban on all short sales, we also appeal to the insights in Comerton-Forde et al. (2016), which provides a more nuanced analysis of short sales by separating passive (buyer-initiated) short sales from aggressive (seller-initiated) short sales in a Glosten and Milgrom (1985) model. The most relevant results for the analysis of the Rule 201 restrictions is that passive short sales are contrarian while aggressive short sales follow price declines. In terms of the specifics of the 201 Regulation, which we will see below, the predictions we obtain from Comerton-Forde et al. (2016), are that the regulation will not affect market makers (in contrast to what is predicted in Boehmer et al. (2008) for example), and that the ban should essentially only affect aggressive short sellers, whether toxic, liquidity, or informationally motivated. Note that we have incorporated toxic trading into the list of aggressive short sellers. These are not considered in Comerton-Forde et al. (2016).

More generally, trading restrictions of any kind tend to generate trade-reducing frictions. However, a positive side effect could be that these restrictions may affect in a disproportionate manner generally toxic trading strategies that are imposing unnecessary intermediation costs. An example of such strategies are those that execute aggressively against standing orders from market-makers that are not fast enough to cancel them as the price is falling (Cartea et al. (2015), Foucault et al. (2017), Aquilina et al. (2020)).

3. Institutional Setting

The Rule 201 shortsale ban prohibits the short selling of any security at or below the national best bid (NBB) if that security's price has fallen below a threshold of 10% relative to the last closing price for all but exempt short sales. On average, more than 95% of short sales for assets included in our analysis are non-exempt.[7]

Once the security's price crosses the threshold, short sale restrictions come into effect. In particular, short sale orders at or below the best bid are immediately prohibited for the asset for the remainder of the current trading day and the whole of the next one. The rule allows for the possibility of an activation on consecutive days. If this happens, the ban extends for an additional trading day after the last trigger. Trading centers are required to comply with the new regulation since February 28, 2011.[8]

The Rule 201 restrictions represent an innovation because the trigger condition is endogenously determined by the market price crossing the 10% threshold. Furthermore, Rule 201 acts as a temporary correction mechanism, that is automatically reverted shortly after its application, which contrasts with previous bans which were in force for much longer time periods.

[7] Exempt short sales are normally part of a hedging trading strategy involving two highly correlated securities, such as different classes of a single company's common equity, two ETF's that track the same index, and so on.

[8] Division of Trading and Markets: Responses to Frequently Asked Questions Concerning Rule 201 of Regulation SHO. Accessed: Sep 28, 2017.

4. Data & Methodology

4.1 Data

We collect the data on Rule 201 bans from the Philadelphia Stock Exchange website, which publishes the list of stocks that trigger the circuit breaker on a daily basis.[9] Our period of study covers observations from January 2016 until December, 2017. We combine data from a number of sources: CRSP, TAQ trades and quotes, Total-View-ITCH, and transaction level short sales provided by FINRA, NASDAQ, NYSE-ICE, and BATS. We match CRSP and TAQ ticker symbols. We retain only common stocks (those with a CRSP share code equal to 11).[10] We require a minimum share price of $2 and at least 50 trades between market open and market close (in total between the NASDAQ and NYSE exchanges) for a stock-day to be included in our sample. We also drop stocks whose identifying information does not allow a merge with both CRSP and Daily TAQ.

Combining data from several sources allows us to provide a general overview of the effects of the Rule 201 restrictions while also providing additional analysis of market conditions for a key venue for which we have more detailed information. The intraday TAQ data is the most comprehensive in terms of trade coverage, and we focus on data during the regular trading day while excluding the minutes closes to the daily open and close. We keep data from 9:40AM–3:50PM EST. Each transaction is timestamped at the millisecond and matched to the prevailing mid-point. TAQ transactions are classified into buyer-initiated (Aggressive Buys, AggB) or seller-initiated (Aggressive Sells, AggS) using the Lee-Ready (1991) algorithm.[11] Individual transaction level information for short sales is obtained from the main four data centers: FINRA monthly files (Nasdaq TRF, New York TRF, and the ADF files), NASDAQ group, NYSE-ICE group, and BATS group. FINRA

[9] https://www.phlx.com
[10] We exclude ETFs, ADRs, Certificates, companies incorporated outside the US, closed-end funds, and REITs.
[11] Chakrabarty et al. (2015) show that this algorithm performs well in modern markets. Nevertheless, there will be noise in this classification given the issues with the precision and coordination of timestamps in the TAQ as discussed in Conrad and Wahal (2020).

and BATS short sale information is posted on their websites, while NASDAQ and NYSE-ICE have given us access to the short sale transaction level data for all short sales that took place on their exchanges.[12] More detailed variables (depth, messages, etc) are constructed using the Total-View-ITCH. Some of our variables are constructed using only NASDAQ data to ensure the reliability of trade direction.

4.2 Methodology

Methodologically, we control for unobserved heterogeneity with a regression discontinuity approach with fixed effects, for observed heterogeneity by pairwise distance matching, and for local effects by constructing a pseudo-trigger for the control group. Our approach is closest to the regression discontinuity design combined with matching used in Halmrast (2015). However, in order to use more recent data, we substitute the pre-regulation period with data from same day (matched) assets that experience similar price drops but did not trigger the restrictions as controls. Barardehi et al. (2024) follow a similar approach although they include all assets that experience a similar price drop on the same day as control group, with added control variables in the regression.

Matching Price Drop: One of the main challenges in analyzing the impact of Rule 201 is that it is triggered by a very unusual event, a 10% price drop relative to the previous day's close ("*the event*"). So the choice of a reference group to serve as counterfactual, as well as the choice of control variables, is very challenging but necessary. We construct the reference group by selecting assets matched in terms of the price drop and asset characteristics to ensure a balance sample between treated and controls such that both have similar characteristics. The first of these characteristics and key for selecting the reference group is the price drop. Short sale restrictions are triggered by a 10% price drop (relative to the previous day's close). We sample asset-days with a maximal price drop of between 9 and 11%,

[12] This data was provided by the exchanges as a courtesy to researchers. The exchanges in the NASDAQ group are: NASDAQ, BX, and PSX, and those of the NYSE-ICE group: NYSE, NYSE-ARCA, NYSE-AMEX.

so that both treated and controls are assets that experience a similar price drop during the day. It also implies that our sample naturally selects assets. First, assets with relatively stable prices do not enter our sample as they do not experience such significant one day price declines. Second, because we only consider single day price drops of between 9 and 11%, we also exclude asset-days with larger price decreases.

Matching Event: In our analysis we want to distinguish the broad impact of short sale restrictions from the unique conditions related to the initiating event. Since a 10% price decline is the criterion for the activation of the short sale restrictions, the identical event cannot be used for assets in the control group. However, considering that our sampling criterion requires that prices for both the treated and control groups do not fall outside the selection window once they enter it, it is plausible to assume that both sets of assets exhibit similar behavior around intraday minimum price levels. Following this logic we select the time each group's price enters the selection window (10% for the treated and 9% for the controls) as the trigger event. For both groups, the triggering event is 1% above the minimum price drop of any asset in the same sample group, whether treated or control. Naturally, we are assuming that absent the Rule 201 trading restrictions both groups of assets would have had similar market behaviour both in the run up to the triggering event and, more broadly, for the remainder of the trading day (we test this assumption in Section 7.).

Matching Assets: To ensure the control group represents a valid counterfactual sample we match treated and control asset-days along other key dimensions. We select treated and control candidates that satisfy the price drop condition on the same day, same time of day, and have the same share code.[13] We require that the event and the control stock in each pair are classified in the same industrial group to account for potential unobservable

[13] We match assets with share code 11 – see footnote 10). For the time of day we divide the trading day intro three intervals: early trading (9:45-11:00), middle of the day (11:00-14:30), end of day trading (14:30-15:45). Recall that we drop asset-days that have an event too close to the market open, at 9:30, and the market close, at 16:00.

sector-wide changes in the informational set.[14] We also exclude asset-days at which a volatility (LULD) halt is triggered.[15]

We also match treated and controls using standard dimensions (market capitalization, trading volume, the stock's average pre-event price, and the average quoted spread). The matching on the four variables is done by minimizing absolute differences in a score function constructed using all four variables. For each of the assets and each variable we keep the ranking of the asset in terms of the percentile in the population, so that each asset is characterized by a vector of four percentile values. We construct the matching score as the average absolute difference between the four percentile values of the treated and control assets, and keep the best control (smallest matching score) subject to the additional constraint that the average absolute difference is less than 10 (out of 100). This procedure leaves us with 954 closely matched pairs (1908 asset-days).

The Matched Sample: To check the matching procedure we first look at the price movements for the two groups of assets, treated and controls. In terms of total return (from the previous day's closing to the current day's closing) we find that there is a small significant difference that is driven by the intraday open-to-close return, which is to be expected from the difference between the maximal price drop between the two.[16] On Table 1 we analyze differences in our matching variables across treatment and control groups. We find the groups to be very similar, the t-tests find no significant differences between the two groups. As our analysis is focused on intraday trading, we limit the horizon of our analysis to intraday market variables during the remainder of the trading day, while markets are open. A detailed analysis of the closing auction, overnight trading, next day trading, and trading after the Rule 201 restrictions are lifted are beyond the scope of this

[14] Classified by the 10 major groups according to their SIC.

[15] We keep assets in the Tick Pilot group but they only represent 5.5% of our sample. The Tick Pilot was implemented for a subset of small cap stocks from September 2016 to September 2018, and increased the tick size from 1 to 5 cents. The effects are studied in a number of papers, see Penalva and Tapia (2021).

[16] We test and reject that this difference is not driving our results using a placebo replication of our analysis comparing assets that experience a drop between 8 and 10% as described below.

paper. Barardehi et al. (2024) study of the overall effectiveness of Rule 201 restrictions.

Econometric Estimation: Our analysis estimates differences-in-differences in a joint panel OLS estimation with standard errors clustered by time-of-day and treated-control matched pair.[17] For the control group we define an equivalent trigger event to distinguish before from after the event. This trigger event is the first time the price hits 9%, which corresponds to a price 1% lower than the minimum for the day (10%) for the control group.

Local Effects: We separate the circumstances surrounding the substantial price drop that is the triggering event from the broader effect of the short sale restrictions during the remainder of the day by including dummy variables for an 11 minute time window around the minute of the event (the *event window* that covers from five minutes before to five minutes after the event).[18] Our choice of time window for the event allows us to compare the actual trigger event and the pseudo-trigger. Additionally, in the placebo analysis, it allows us to identify market conditions around significant price declines for asset groups unaffected by short sale restrictions. Across all samples, the differences we observe are minor. However, market conditions around the event display significant changes in microstructure variables both statistically and economically (refer to Figure 1 and Section 6. for further details).

Controls for Large Price Movements: Our sample selection criterion, assets that experience a significant price drop, implies that we are observing assets that experience unusually high volatility days. In order to control for the effects of unrelated price movements on the variables of interest we introduce controls for the size of the movement in the price from the start to the end of the minute. We introduce these controls in the form of price movement fixed effects, by including dummies for within-minute

[17] Each pair of treated and control pairs is identified by the variable MatchID.

[18] The motivation to analyze separately the local, event specific, changes and the broader effects of the regulation is motivated by existing results in the literature that find that regulation triggered by market conditions, such as volatility halts or trading pauses, may be accompanied by specific market reactions, such as for example the magnet-effect (Abad and Pascual (2007), Goldstein and Kavajecz (2004), Sifat and Mohamad (2020)). These effects are considered in detail for the 201 restrictions below, in Section 6.

price changes in the following 22 intervals: $(-\infty, -10\%]$, $(-10, -9\%]$, $\ldots$, $(9, 10\%]$, $(10\%, \infty)$. The resulting dummies allow us to control for unusual trading conditions arising from large price moves that are not associated with the application of Rule 201, and which have been associated with unusual volume and isolated toxic order flows (see Easley et al. (2012)).

Regression Equation: The main specification of the panel data regression we run also includes time-of-day fixed effects every half-hour, and is described by the following equation:

$$Y_{i,t} = \alpha_i + \beta_1\, Drop + \beta_2\, Drop \times 201Rule + \sum_{j=-5}^{5} (\delta_j T_{j,t} + \eta_j T_{j,t} \times 201Rule)$$
$$+ \sum_{j=1}^{13} \kappa_j H_j + \sum_{j=-10}^{11} \gamma_j Dum_{r_{i,t} \in [R_{j-1}, R_j]} + \varepsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ denotes the variable of interest for asset-date i in minute t. We analyze a number of microstructure related variables defined in detail in section 1. of the Appendix. Our main parameters of interest are β_1 and β_2. The parameter β_1 captures the baseline effect on both treated and control assets after the large price drop that defines the triggering event. This event is either the application of the restrictions for the treated group, or the price dropping by 9% for the control stocks. The parameter β_2 captures the differential effect of the treated group, and the impact of the Rule 201 restrictions on the variable of interest.

The parameters $(\delta_j)_{j=-5}^{5}$ and $(\eta_j)_{j=-5}^{5}$ capture the transitory dimension in the minute of the event as well as the five minutes immediately surrounding the event, before and after. Like β_2, the η_j parameters capture the differential effect of the treated group, and hence the impact of the Rule 201 restrictions. The γ_j coefficients capture the fixed effects for the magnitude of the change in the price during the current minute, modelled as the 22 dummies ($Dum_{r_{i,t} \in [R_{j-1}, R_j]}$) described above. The coefficients α_i and κ_j capture the matched asset-day pair and the (half-hourly) time fixed effects, respectively.

Outliers: We winsorize variables at the 0.5 and 99.5 per cent levels to limit the influence of outliers, and standardize most variables. We use standardization in order to avoid issues with the scaling of the variables and to facilitate the interpretation of coefficients. The coefficients measure changes in the variables of interest in terms of standard deviations from the mean for each stock-day.[19] Variables like returns and market share, that are naturally comparable across assets, are not standardized.

5. Rule 201 Restrictions: Effectiveness and Mechanism

In this section we present the results of the overall effects of the Rule 201 restrictions. These results are organized to first measure the effectiveness of the restrictions by looking at their direct impact on short sales, volume, and price pressure. After establishing the significance of the restrictions, we test the validity of different theories by examining their predicted impact on key market microstructure variables. This allows us to identify the channels through which the restrictions influence trading behavior and market quality. Further analysis through additional variables is included at the end of the Section, and additional details are included in the Internet Appendix. Summary statistics for the main variables used in the analysis, as well as a summary of the economic significance of the results is included in the Internet Appendix.

5.1 Are the Restrictions Effective?

We start by looking at short selling activity directly (Table 2). We find that Rule 201 negatively affects both aggressive and passive (non-exempt) short sales. On the other hand, exempt short sales increase but not enough to compensate the effect on exempt short sales.

The reduction in short sales is accompanied by lower volume (Table 2), and in particular, aggressive sell volume, thereby reducing downward pressure on prices. We also document that for the assets in our sample this

[19] Moments are computed using the in-sample means and standard deviations. The use of the in-sample means is standard practice in all panels with fixed-effects, and the use of the in-sample standard deviation will, if anything, bias against finding significant differences, given that the sample stock-days have unusually high intraday volatility.

phenomenon would have happened in the absence of the 201 Rule as well: aggressive buys increase significantly and aggressive sales decrease (though not significantly) for all the assets in our sample. However, our design identifies the differential effect of the regulation: the Rule 201 has an additional impact on volume traded, reducing volume on both sides, but primarily by reducing aggressive sales: Rule 201 increases the reduction in aggressive sales by an order of magnitude (from -0.016 to $-0.11 = -0.016 - 0.094$ see Table 2), and reduces the increase in buying pressure from aggressive buys by half.

On Table 2, we look at whether this reduction in price pressure translates into greater returns. As expected, the price of the assets in our sample recover partially after the event, consistently with the evidence in Florindo (2021), Jain et al. (2012), and Barardehi et al. (2024). We find that this rebound lasts for the whole of the trading day and is greater in the treated group.

Combining these results, we find that Rule 201 is effective in reducing sellers' price pressure, which leads to a slowdown in the stock price decline. This effectiveness is observed despite the rule's limited restrictions on trades–it only bans short-sales at or below the best bid-and the exemptions it includes.

5.2 The Effect on Trading Strategies and Market Quality: Testing the Theoretical Models

Beyond its effectiveness in reducing price pressure, we are interested in how the restrictions affect trading and market quality. We appeal to existing theories. These theories differ on the motivation behind the trades that are affected by the restrictions, and how the market reacts to the reduced presence of such trades.

The model in Comerton-Forde et al. (2016) argues that market makers use short-sales only passively and primarily after price increases that leave them without an inventory in the affected stocks. In principle, Rule 201 will not affect market-makers directly as passive sales on the ask side are unaffected. Furthermore, because the Rule 201 is triggered after a significant price decline, market makers providing liquidity will have accumulated a long position in the stock and will no longer have a need to short-sell, even if they wanted to sell aggressively.

To confirm that market making activities are not affected we look at measures of market-making activity, depth and spreads, in Table 3, where we find an improvement in both. Quoted and effective spreads decrease, while the effect on depth measures is significant on the Ask side. In particular, the decrease in depth at the best offer (Ask) and at five cents from the best (Ask + 5c) is reversed in the treated group. On the Bid side we find little difference between treated and controls. Thus, we find that overall market-making activity increases, improving liquidity. Furthermore, these results are inconsistent with the models that argue that short-selling restrictions will have a significant effect on short sales from uninformed liquidity demanding traders (Diamond and Verrecchia (1987); Boehme et al. (2006)). A significant reduction in uninformed liquidity demanding trades would reduce the amount of uninformed trading, increasing the expected cost of market-making, and leading to the opposite effect: higher spreads and less depth.

This leaves two types of theories as possible explanations: those that look at informed short sales (Comerton-Forde et al. (2016), Diamond and Verrecchia (1987)), and those that look at toxic (Brunnermeier and Oehmke (2013), Foucault et al. (2017)) traders as candidates for affected trades. A drop in the number of trades from these participants reduces the cost of market-making, and is consistent with the observed results.

A key difference between toxic short-sellers and informed ones is the informational content of their trades. Hong and Stein (2003) points out that removing informed traders via a short sale ban does not invalidate the information driving these trades, just delays the incorporation of the information into prices, and leads to substantial future price drops. Lacking a standard measure for capturing these delayed price drops, we look at the distribution of overnight returns for the night after the restrictions come into effect (from the price at the close on the date the restrictions come into effect to the price at the open on the next trading day). We test for the presence of delayed incorporation of negative information into prices by testing whether the restricted assets are overrepresented in the lower tail of the distribution (bottom decile). The result of this novel test is that of the 190 assets in the tail, 82 are controls and 108 are treated assets (the difference in the distributions is significant with a p-value of 0.028 using a 1-sided Fisher's exact test). This evidence supports the hypothesis that the Rule 201 has a significant effect on informed short sales.

Traditional measures of price informativeness (price impact, Amihud, autocorrelation, and variance ratios) provide mixed results. The impact of Rule 201 on price informativeness varies depending on the estimation method and time horizon. In Table 3 we find a reduction in the price impact component in effective spreads at the shortest, 100ms and 1min, horizons, and an increase at the longest, 5min, horizon. In Table 4 we look at two other measures related to the information content in prices (Goyenko et al. (2009)): the autocorrelation of 1 minute returns and the Amihud illiquidity ratio. We find no significant increase in the former and a decrease in the latter (statistically significant when measured over 1 min intervals). We also consider variance ratios in Table 4, and find lower Variance Ratios (at 5 and 10 minutes) which are associated with an improvement in price efficiency. These results suggest that the 201 Rule favors traders with longer lived informational advantages (beyond 5 minutes), to the detriment of traders with shorter lived informational advantages (less than one minute).

Thus, what we find is that the Rule 201 restrictions delay the incorporation of information into prices, reducing informed trading (as put forth in Comerton-Forde et al. (2016), Diamond and Verrecchia (1987)), but the impact is greater on toxic trades, whether they have a very short lived informational advantage (Foucault et al. (2017)), or none at all (Brunnermeier and Oehmke (2013)), than on longer lived informational trades. Our evidence on overall price efficiency is mixed, with improvements in the long-term variance ratio accompanied by greater overnight price drops.

We look for further evidence along this lines by looking at measures of HFT activity, as these trades are (at least in part) associated with toxic order flow in a number of theoretical and empirical studies (Cartea et al. (2019), Aquilina et al. (2020), or Brogaard et al. (2017)). Consistently with our interpretation of the effects on informational trades, we find, 3, that measures of algorithmic activity decline once the ban is active.

5.3 Further Supporting Evidence and Results

The evidence suggests that the impact of the Rule 201 restrictions is consistent with a decline in informed trading, which is stronger on toxic trades with shorter lived or no informational content, including trades from HFTs. We hypothesize that patient traders with long-lived informational advantages may be less affected because they can continue to sell short using less aggressive orders. Firstly, the restrictions do not apply to (passive) short sales at prices above the bid. Secondly, a reasonable hypothesis is that those that invest in acquiring long-lived information will be sufficiently sophisticated to be able to execute alternative contrarian strategies that do not require aggressive short sales of the affected stocks (as proposed in Kolasinski et al. (2013)).

To evaluate the first channel we look at the gains for passive trading in terms of realized spreads, in Table 5, where the results are consistent with our hypothesis. We find an increase in realized spreads at short horizons, consistent with a decline in short-lived informational and toxic trades. On the other hand, at longer horizons realized spreads decline.

Another effect of traders switching from aggressive to passive short sales is lower volume, as passive short selling eliminates the need for additional intermediation trades from market makers (see Cartea and Penalva (2012)). We did find lower volume, Table 2, but this is also consistent with increased trading frictions and costs from the restrictions. So we look at depth, in Table 3, and we find, consistent with the shift to passive trading, that depth at the ask increases.

In terms of the second channel, most of these assets do not have liquid derivatives, so we look for evidence of changes in equity execution strategies. The literature (Chao et al. (2018), Comerton-Forde et al. (2019)) propose that short sellers may consider rebate chasing in response to the 201 Rule restrictions. To test this we look for evidence of changes in routing strategies in the market shares of different trading venues on Table 5, where we separate venues into the asset's primary exchange ("QuotingX") and lit pools with inverted fee schedules ("Inverted", taker-maker exchanges BATY, NASDAQ-BX, EDGE-A.). The results do no support re-routing from the quoting exchange to inverted fee venues, as there is no significant differences between the changes in the market share of the quoting exchange and that of the inverted fee ones.[20]

We also look for changes in the transparency of trading strategies by looking at both hidden orders in organized exchanges, and shifts to off-exchange venues, specially those using mid-point execution. For trading off-exchange we use the total volume marked "FINRA" in the TAQ data.[21] Surprisingly, on-exchange transparency improves: we find a small but significant drop in hidden orders (Table 5). But, we do find a significant shift in the percentage of trades executed off-exchange (Table 5) as the market share of the quoting exchange falls and while that of dark pools (FINRA) increases significantly for both sales and purchases. Surprisingly, on-exchange transparency improves: we find a small but significant drop in hidden orders (Internet Appendix). But, we do find a significant shift in the percentage of trades executed off-exchange (Table 5) as the market share of the quoting exchange falls and while that of dark pools (FINRA) increases significantly for both sales and purchases.

Finally we consider effects of the regulation on other dimensions of importance for regulators, namely volatility. The evidence we find is consistent with the effects we have found for liquidity, namely with an improvement of market conditions associated with a reduction in informed and toxic trades.

In terms of volatility, fewer informational and toxic trades will lead to lower risks for passive orders, so we expect bid-ask prices to be less sensitive to market events, and less volatile. We find this when we look at intra-minute price variation in Table 5, and the standard deviation of 1 minute returns,

[20] The market share of inverted fee venues mirrors the changes in the market share of the quoting exchange, but with smaller, sometimes insignificant, coefficients.

[21] The TAQ dataset reports trading reported to regular exchanges from those reported to FINRA. The volume reported to FINRA is between 40-60% of the asset's total daily volume and comes from dark trading venues: ECNs, internal broker crossings, etc.

Table 4. As we have documented a drop in volume, which is known to be associated with lower volatility (Jones et al. (1994) or Gallant et al. (1992)), we extend our baseline analysis with additional controls for volume changes, and the reduction in volatility persists.[22]

In conclusion, we find that Rule 201 is effective in reducing selling pressure and slowing down price drops. We also find that it is accompanied by increased liquidity and reduced informed trading, specially from trades with very short-term or no informational advantages. Furthermore, these results are accompanied by changes in trading strategies that become more passive and/or re-rout orders to dark venues.

6. The Local Impact: Endogenous Triggers and the Magnet Effect

In this section we briefly explore the dynamics of the main variables around the minutes immediately before and after the activation of the restrictions.

A key characteristic of the Rule 201 restrictions is that they are activated by market events, and hence are endogenously determined by market conditions. This type of activation rule has been (and continues to be) used by regulators in other contexts, such as to trigger circuit breakers or volatility stops, and has been studied in various papers, among others in Miller (1989), McMillan (1990), Madhavan (1992), Abad and Pascual (2007), Hsieh et al. (2009), and Hautsch and Horvath (2019). The literature focuses on the presence or absence of a "magnet effect". By magnet (or gravitational) effect we refer to the phenomenon whereby the presence of a rule-based triggering

[22] Given our narrow window of observation we cannot estimate conditional volatility as in Jones et al. (1994) or Gallant et al. (1992). We introduce volume (contemporaneous and lagged) as a control variable in our panel estimation. In unreported results, we replicate equation 1 including Total (log) TAQ volume interacted with the diff-in-diff dummies, and the lagged Total (log) TAQ volume as controls. From the resulting regression results we obtain that the lower volatility under the 201 restrictions, is primarily due to the change in the positive relationship between volume and volatility after the event. In particular, this relationship is weaker after the event and not significantly different between treated and control assets.

event generates (attracts) actions that ultimately accelerate (or decelerate) its triggering.

As we have discussed previously, using a matched sample of stocks that experience a similar price drop allows us to isolate the effect of the Rule 201 restrictions. We further isolate the local effects around the price drop by defining an event similar to the Rule 201 trigger but for the control group. We evaluate the validity of our design using a placebo comparison, which we discuss in detail in Section 7. What we find is that the local effects we identify are the same in the treated and the control groups. Although the triggering event has significant effects on key microstructure variables (volume, volatility, spreads, etc), we find no evidence of differences between treated and control groups, and hence find no evidence of a magnet or gravitational effect associated specifically with the triggering of the Rule 201 restrictions.

The analysis of local effects is included in the same tables where we summarize the overall effects of the Rule 201 restrictions discussed in the previous section (Tables 2-5). The rows to look at are:

- row "Event Minute (δ_0)": this is the coefficient for the baseline effect for both treated and control stocks on the minute the event is triggered.
- row "Event Minute $\times$ 201 (η_0)": this is the coefficient for the interaction term of the minute of the event with the treatment indicator.

In addition, the internet appendix includes the equivalent coefficients for each of the five minutes before and after the event (and we refer to these tables in brackets when we refer to the minutes surrounding the event minute). In order to assist the reader, we present the essential information graphically in Figure 1. This figure contains a significant amount of information, some of which we will not use until the next section.

Figure 1 summarizes the main results. The figure is divided into five subfigures, one for each of the key variables: the asset's return, volatility (intra-minute difference between midprice high and low), quoted spread, and volume and short sales affected by the restrictions, namely volume on the bid side and non-exempt short sales on or below the bid price. In total, each subfigure includes 12 pairs of coefficients, separated by a dashed line. These coefficients capture average effects in the variable of interest (without distinguishing treated and control). The interaction coefficients identifying differences between treatment and control groups are not included in this Figure. However, visualizing them is relatively uninteresting as for the most part they are statistically insignificant.

The coefficients displayed correspond to two analysis, and hence are plotted in pairs, one in blue on the left labelled *xt201* for the main analysis, and the other in red on the right for the placebo analysis, which we discuss in the next section. Each subfigure splits the coefficients into two groups using a dashed line. The coefficients to the left of the dashed line are the baseline coefficients capturing the broad effects after the event. These coefficients are the baseline effects for the whole sample, without distinguishing between treated and control groups, which we have not discussed in previous sections where we focused exclusively on the relative differences between the treated and control groups.

The coefficients to the right of the dashed line describe the local effects we want to discuss in this section. In particular, we have the coefficients of the 11 (pairs of) δ_t dummies. Each δ_t coefficient corresponds to the dummy for each one of the minutes around and including the triggering event: five minutes before, the minute of the event, and five minutes after the event.

What we can see in the Figure is that there are significant changes in market conditions surrounding the immediate triggering of the restrictions both for the Rule 201 stocks and the control group. Also, the peak effects are observed in the minute following the triggering event.

Firstly, Figure 1a illustrates how the triggering event occurs in the context of a significant local price drop, which does not last passed the first minute after the price drop. In the following minutes, returns for all assets are close to zero but significantly positive, implying a partial price rebound. These local price dynamics suggest that prices around the trigger event are not purely random and include a certain degree of momentum for all groups, both negative before and positive after. This suggests a novel hypothesis, namely that that a magnet effect might occur for the chosen group, yet not in relation to the Rule 201 trigger, but rather upon the occurrence of entering the sampling window.

Exploring this idea further along other dimensions, on Figure 1b we look at non-exempt short sales. What we find is that accompanying the price drop there is a gradual increase in short sales. These higher than average short sales do not disappear, but continue to be positive past the time when average returns have become positive.

We observe a pattern similar to the one observed in the affected short sales when looking at most directly affected volume (the one on the bid) and volatility, in Figures 1c and 1d. Volume on the bid and volatility increase with the price drop. We find differences after the change in price dynamics. In the case of volume, after the peak price changes, volume returns to normal levels. On the other side, volatility drops but it does so gradually and by the end of our observation window (of five minutes) has not returned to normal levels.

Finally, quoted spreads, in Figure 1e, display a distinctly different dynamics. The level of the quoted spreads is higher than usual during the price drop, but this level does not change significantly during the price drop. However, following the price drop there is a shift, the level increases further and stays higher than during the price drop for the remainder of our observation window.

Overall, we find no evidence of a magnet effect for the Rule 201 restrictions, but we find evidence of significant and meaningful changes in the key variables of interest around the event of entering our sampling window. This event can be described as being close to the day's minimum for both treated and control stocks, and coincides with higher than usual price declines, short selling activity, volume, volatility, and quoted spreads. However, we find that after the price decline, the subsequent (small) positive returns are not accompanied by a reversal in the other variables. Volume, short sales, and volatility gradually return to normal levels. The reaction in volume is quicker than in short sales, and volatility is the slowest one. Quoted spreads on the other hand display a significantly different pattern. Not only do spreads not return to normal but they become wider, suggesting that the pressure on liquidity following the price decline leaves a significant negative impact on liquidity provision, both for treated and control stocks alike, that lasts the length of our observation window, but also for the remainder of the day.

In contrast with the average effects for both treated and control stocks, we find that the differential effect between treated and control stocks, captured by η_0, is (mostly) insignificant. The magnitude of the effects surrounding the triggering event is not statistically different for treated and control groups, hence not driven by the triggering of the Rule 201 restrictions.

7. Discussion of the Methodology

As outlined in the Methodology section, our identification strategy is based on the argument that the control group is a valid representation of the counterfactual behavior of the treated assets in the absence of the Rule 201. This argument has two components to it. The first is common to all regression discontinuity identification strategies, namely that the treatment and control assets are essentially identical both in the general properties of the stock (the financial instrument), and specifically under the circumstances that we use to select them into the sample.

To control for the general characteristics of the stock, we have matched treatment and control stocks on the usual microstructure dimensions (market capitalization, volume, price, and quoted spread). The validity of the matching between stocks is standard in the empirical microstructure papers. If anything, our matching procedure is more precise by including quoted spreads, when most matchings are done using market capitalization, and industry (O'Hara et al., 2018).

The sampling criteria used to select the stock-days in the treatment and control samples is that the stock experiences a price drop of around 10% relative to the closing price the previous day. We argue that the difference between experiencing a price drop between 10 and 11% and drop between 9 and 10% are essentially random, and that the observed differences between treatment and control stocks is driven entirely by the Rule 201 restrictions. The previous analysis of the local effects already points to the insignificance of the local differences between the two groups surrounding the triggering event. To identify the local effects of the trigger, the 10% price drop, we created a pseudo-trigger for the control group at the first time the stock price crosses the 9% price drop threshold. As we argued in the methodology section, we consider these two events as equivalent as thresholds relative to the maximum price drop used for inclusion in the treatment or control stock-day groups.

To address the validity of our arguments, we run a placebo analysis, comparing our pool of control stocks (those with a maximum price drop that is between 9 and 10%) to matched stocks on days with a maximum price drop that is between 8 and 9%. The first group we label as the P-treated, and the second group as the P-control group. We create the pseudo-trigger for the P-control group using the same logic as for the P-treated, that is, we use the moment the price enters the sampling window (8% price drop) for the first time as the pseudo-trigger of the P-control group. We then repeat the regressions we run in the main analysis comparing the P-treated with the P-control groups. The resulting comparison of coefficients provide strong evidence in favour of the validity of our identification assumptions as well as for the presence of a specific microstructure event for our sample assets at the time of the (pseudo) trigger.

We focus the presentation on the five key variables used to discuss the local effects, and compare the coefficients for the placebo and the main analysis on Figure 1. The results with all the coefficients and t-statistics is available in the Internet Appendix. Figure 1 includes the average post event coefficient (on the left of the dashed lines) and the local effects, to the right, in pairs. Each pair of coefficients is made up of the coefficient of the main analysis on the left (in blue) and the same coefficient in the placebo analysis on the right (in red).

Overall, in the placebo analysis we find significant local effects around the pseudo-trigger for both groups, and no significant differences between the P-treated and P-control groups. The local effects around the event replicate the ones in the main analysis we have described in the previous section: there are significant changes leading and including the price decline around the trigger event. These changes are followed by a reversal in all variables but the quoted spread, and at different speeds. Changes in quoted spreads suggest a significant and persistent negative impact on liquidity for the remainder of the day. However, we find no statistically significant differences in the coefficients comparing the two groups, either in the main post-event coefficients, or in the local effects. Therefore, the conclusion from the placebo analysis is that there is strong evidence that the research design identifies the causal effects we are interested in, an does so separately identifying the effect of the large price drop from the effect of the Rule 201 restrictions. Furthermore, the sampling procedure identifies a significant microstructure event at the first time the selected assets' price crosses the threshold used to define the sampling window. We want to emphasize here, that there is no a priori theoretical or statistical reason why the first time the price of an asset crosses this threshold should be of particular significance, specially across the three different sample groups we have studied (P-controls, controls/P-treated, and treated groups). However, the causes for this phenomenon are a question for future research.

8. Conclusions

Between 2010 and 2011 the SEC went beyond broad bans and generic restrictions, and designed and implemented market-driven, short lived, and targeted restrictions on short sales, collectively referred to as the Rule 201. In this paper we have provided a novel evaluation of the effects of these short sale restrictions using a solid theoretical framework, two years of intraday data, a broad gamut of market microstructure indicators, and a careful identification strategy that separately identifies the effects of the Rule 201 restrictions and those of the large price drop that triggers it.

We find that within our window of analysis the regulation achieves its objectives: liquidity improves in lit venues and prices become more stable. We find evidence that the regulation achieves this by reducing downward price pressure, and the toxicity of order flow in these venues, without imposing significant burdens on market making strategies. This is accompanied by a movement of short sale volume from lit exchanges to dark pools and a reduction in overall volume. The incorporation of negative information appears to be partially reduced, though price informativeness improves at longer (5-minute) horizons, possibly as a result of a change in the mix of informed trading. Furthermore, we find that the circumstances surrounding the event that triggers the regulation (the 10% price drop) are unusual market circumstances, but we find that these circumstances are not due to the regulation, as we also find them in the control and placebo groups.

Our analysis is consistent with the regulation generating costs for short selling that are concentrated on toxic short sales. This short selling appears to come primarily from two sources. The first is uninformed short sellers whose toxicity comes primarily from the accumulated price pressure already present on the asset at the time of the trigger. We hypothesize that these traders either withdraw or significantly reduce their desired short positions. The second type of affected short selling appears to come from strategies with very-short lived informational advantages. These are present in general, and are toxic in the sense described in Foucault et al. (2017). However, the restrictions remove them from the bid side of the book, lowering the cost of liquidity provision. In contrast, informed traders with longer-lived information appear to be less affected and increase their relative importance. Market making activity is unaffected in the sense that overall liquidity benefits from the restrictions. We conclude that the Rule 201 restrictions set a new standard for effective actions to deal with toxic short selling strategies for assets facing large price declines.

References

Abad, D. and Pascual, R. (2007). On the magnet effect of price limits. *European Financial Management*, 13(5):833–852.

Alexander, G. J. and Peterson, M. A. (2008). The effect of price tests on trader behavior and market quality: An analysis of reg sho. *Journal of Financial Markets*, 11(1):84–111.

Aquilina, M., Budish, E. B., and O'Neill, P. (2020). Quantifying the high-frequency trading "arms race": A simple new methodology and estimates. *Chicago Booth Research Paper*, (20-16).

Barardehi, Y., Bird, A., Karolyi, S., and Ruchti, T. (2024). Are short-selling restrictions effective? *Management Science*.

Battalio, R. and Schultz, P. (2011). Regulatory uncertainty and market liquidity: The 2008 short sale ban's impact on equity option markets. *The Journal of Finance*, 66(6):2013–2053.

Beber, A., Fabbri, D., Pagano, M., and Simonelli, S. (2020). Short-Selling Bans and Bank Stability. *The Review of Corporate Finance Studies*, 10(1):158–187.

Beber, A. and Pagano, M. (2013). Short-selling bans around the world: Evidence from the 2007–09 crisis. *The Journal of Finance*, 68(1):343–381.

Boehme, R. D., Danielsen, B. R., and Sorescu, S. M. (2006). Short-sale constraints, differences of opinion, and overvaluation. *Journal of Financial and Quantitative Analysis*, 41(2):455–487.

Boehmer, E., Jones, C. M., and Zhang, X. (2008). Unshackling short sellers: The repeal of the uptick rule. *Columbia Business School, unpublished manuscript, December.*

Boehmer, E., Jones, C. M., and Zhang, X. (2013). Shackling short sellers: The 2008 shorting ban. *The Review of Financial Studies*, 26(6):1363–1400.

Boehmer, E. and Wu, J. (2012). Short selling and the price discovery process. *The Review of Financial Studies*, 26(2):287–322.

Boulton, T. J. and Braga-Alves, M. V. (2010). The skinny on the 2008 naked short-sale restrictions. *Journal of Financial Markets*, 13(4):397–421.

Brogaard, J., Hendershott, T., and Riordan, R. (2017). High frequency trading and the 2008 short-sale ban. *Journal of Financial Economics*, 124(1):22–42.

Brunnermeier, M. K. and Oehmke, M. (2013). Predatory short selling. *Review of Finance*, 18(6):2153–2195.

Cartea, Á., Jaimungal, S., and Penalva, J. (2015). *Algorithmic and High-Frequency Trading*. Cambridge University Press.

Cartea, Á., Payne, R., Penalva, J., and Tapia, M. (2019). Ultra-fast activity and intraday market quality. *Journal of Banking & Finance*, 99:157–181.

Cartea, Á. and Penalva, J. (2012). Where is the value in high frequency trading? *Quarterly Journal of Finance*, 2(3):1–46.

Chakrabarty, B., Moulton, P. C., and Shkilko, A. (2012). Short sales, long sales, and the lee–ready trade classification algorithm revisited. *Journal of Financial Markets*, 15(4):467–491.

Chakrabarty, B., Pascual, R., and Shkilko, A. (2015). Evaluating trade classification algorithms: Bulk volume classification versus the tick rule and the lee-ready algorithm. *Journal of Financial Markets*, 25:52–79.

Chao, Y., Yao, C., and Ye, M. (2018). Why Discrete Price Fragments U.S. Stock Exchanges and Disperses Their Fee Structures. *The Review of Financial Studies*, 32(3):1068–1101.

Comerton-Forde, C., Grégoire, V., and Zhong, Z. (2019). Inverted fee structures, tick size, and market quality. *Journal of Financial Economics*, 134(1):141–164.

Comerton-Forde, C., Jones, C. M., and Putniņš, T. J. (2016). Shorting at close range: a tale of two types. *Journal of Financial Economics*, 121(3):546–568.

Conrad, J. and Wahal, S. (2020). The term structure of liquidity provision. *Journal of Financial Economics*, 136(1):239–259.

Davis, R. L., Jurich, S. N., Roseman, B. S., and Watson, E. D. (2017). Short-sale restrictions and price clustering: Evidence from sec rule 201. *Journal of Financial Services Research*, pages 1–23.

Diamond, D. W. and Verrecchia, R. E. (1987). Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics*, 18(2):277–311.

Diether, K. B., Lee, K.-H., and Werner, I. M. (2009). It's SHO time! Short-sale price tests and market quality. *The Journal of Finance*, 64(1):37–73.

Easley, D., López de Prado, M. M., and O'Hara, M. (2012). Flow toxicity and liquidity in a high-frequency world. *Review of Financial Studies*, 25(5):1457–1493.

Fang, V. W., Huang, A. H., and Karpoff, J. M. (2016). Short selling and earnings management: A controlled experiment. *The Journal of Finance*, 71(3):1251–1294.

Florindo, O. H. (2021). *Three essays on short selling bans, asset pricing and market quality*. PhD thesis, Universidad Carlos III de Madrid.

Florindo, O. H., Penalva, J., and Tapia, M. (2022). Operate, not amputate: A surgical approach to dealing with toxic short selling. *Available at SSRN 4096575*.

Foucault, T., Kozhan, R., and Tham, W. W. (2017). Toxic arbitrage. *The Review of Financial Studies*, 30(4):1053–1094.

Gallant, A. R., Rossi, P. E., and Tauchen, G. (1992). Stock Prices and Volume. *The Review of Financial Studies*, 5(2):199–242.

Glosten, L. R. and Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1):71–100.

Goldstein, H. and Healy, M. J. (1995). The graphical presentation of a collection of means. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 158(1):175–177.

Goldstein, M. A. and Kavajecz, K. A. (2004). Trading strategies during circuit breakers and extreme market movements. *Journal of Financial Markets*, 7(3):301–333.

Goyenko, R. Y., Holden, C. W., and Trzcinka, C. A. (2009). Do liquidity measures measure liquidity? *Journal of financial Economics*, 92(2):153–181.

Grullon, G., Michenaud, S., and Weston, J. P. (2015). The real effects of short-selling constraints. *The Review of Financial Studies*, 28(6):1737–1767.

Halmrast, N. (2015). *Essays in financial economics and banking*. University of Toronto (Canada).

Hautsch, N. and Horvath, A. (2019). How effective are trading pauses? *Journal of Financial Economics*, 131(2):378–403.

Hong, H. and Stein, J. C. (2003). Differences of opinion, short-sales constraints, and market crashes. *The Review of Financial Studies*, 16(2):487–525.

Hsieh, P.-H., Kim, Y. H., and Yang, J. J. (2009). The magnet effect of price limits: A logit approach. *Journal of Empirical Finance*, 16(5):830–837.

Jain, C., Jain, P., and McInish, T. H. (2012). Short selling: the impact of sec rule 201 of 2010. *Financial Review*, 47(1):37–64.

Jones, C. M., Kaul, G., and Lipson, M. L. (1994). Transactions, Volume, and Volatility. *The Review of Financial Studies*, 7(4):631–651.

Kolasinski, A. C., Reed, A., and Thornock, J. R. (2013). Can short restrictions actually increase informed short selling? *Financial Management*, 42(1):155–181.

Lee, C. M. and Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, 46(2):733–746.

Losada-Lopez, R. and Martinez-Pastor, A. (2020). Analisis del efecto de las restricciones sobre la operativa en corto sobre acciones españolas entre marzo y mayo de 2020. *CNMV working paper*.

Madhavan, A. (1992). Trading mechanisms in securities markets. *The Journal of Finance*, 47(2):607–641.

Marsh, I. W. and Payne, R. (2012). Banning short sales and market quality: The uk's experience. *Journal of Banking & Finance*, 36(7):1975–1986.

McMillan, H. (1990). *Circuit breakers in the S & P futures market: Their effect on volatility and price discovery in October 1989*. University of Rochester.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of Finance*, 32(4):1151–1168.

Miller, M. H. (1989). Commentary: Volatility, price resolution, and the effectiveness of price limits. In *Regulatory reform of stock and futures markets*, pages 103–105. Springer.

O'Hara, M., Saar, G., and Zhong, Z. (2018). Relative tick size and the trading environment. *The Review of Asset Pricing Studies*, 9(1):47–90.

Penalva, J. S. and Tapia, M. (2021). Heterogeneity and competition in fragmented markets: Fees vs speed. *Applied Mathematical Finance*, 28(2):143–177.

Sifat, I. M. and Mohamad, A. (2020). A survey on the magnet effect of circuit breakers in financial markets. *International Review of Economics & Finance*, 69:138–151.

Switzer, L. N. and Yue, H. (2019). Effects of the short sale circuit breaker on the stock market. *Journal of International Financial Management & Accounting*, 30(3):250–274.

Tables and Figures

Table 1 - Treated vs Controls

The table reports the t-tests of differences between the matching variables for the treatment and control groups, as well as daily returns. Daily return is the return from the previous market close to the current day's market close, the overnight return is the return from the previous market close to the current day's market open, and the intraday return is the return from the current day's market open to the current day's market close.

	Control	Treated 201	Difference	t-stat	p-value
Market Capitalization ('000) (in logs)	12.15	12.14	-0.008	0.106	0.916
Volume (log dollars)	13.1	13.06	-0.033	0.367	0.714
Price	8.3	8.45	0.151	-0.324	0.746
Quoted Spread† (cents)	6.80	7.42	-0.62	-1.299	0.903
Moments of daily returns: standard deviation	12.26	9.2	-3.058	1.618	0.106
Moments of daily returns: skewness	0.44	0.41	-0.035	0.465	0.642
Moments of daily returns: kurtosis	6.96	6.58	-0.38	1.171	0.242
Return (daily)	-5.93	-6.66	-0.73	4.339	0.000
Return (overnight)	-0.97	-1.08	-0.114	0.95	0.342
Return (intraday)	-4.95	-5.57	-0.62	3.041	0.002

† The *QuotedSpread* variable includes three very large outliers. The t-test in this table is done without these outliers. Including the outliers does not change the qualitative results but provides highly distorted values of the sample statistics–these are available upon request.

Table 2 - Rule 201: Effectiveness

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are different metrics of short selling activity, volume, and returns. Short-sale data for the ALL MARKETS analysis is provided by FINRA, CBOE, NYSE-ICE, and NASDAQ groups, and aggregated. All variables are standardized by the in-sample mean and standard deviation for each asset-day. * As returns are naturally comparable across assets, they are not standardized. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

Variable	Mean	St dev	Post Event (β_1)	Diff-in-Diff (β_2)	% change	Observations	R-squared
Passive NE SS	1.05	1.89	0.052***	-0.067***	-12.0%	707,868	0.017
Aggressive NE SS	1.96	2.49	0.028**	-0.264***	-33.6%	707,868	0.053
Non-Exempt SS	2.31	2.63	0.030***	-0.233***	-26.6%	707,868	0.048
Exempt SS	0.25	0.93	-0.018***	0.300***	112.8%	707,868	0.019
Short Sales (Total)	2.39	2.68	0.023*	-0.170***	-19.1%	707,868	0.051
Log Sell Volume (TAQ)	5.05	2.94	-0.016	-0.094***	-5.5%	707,497	0.080
Log Buy Volume (TAQ)	4.62	2.93	0.092***	-0.043**	-2.7%	707,497	0.051
Log Volume (Total, TAQ)	6.02	2.82	0.035**	-0.076***	-3.6%	707,497	0.079
Return (bps)*	-1.18	44.69	5.821***	0.734***	73 bps	707,868	0.009

Table 3 - Market Quality and Informativeness

The table reports the coefficients from the estimation of the model described in equation 1. All variables are standardized by the in-sample mean and standard deviation for each asset-day. * As trade-to-order ratios are naturally comparable across assets, they are not standardized. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

Variable	Mean	St dev	Post Event (β_1)	Diff-in-Diff (β_2)	% change	Observations	R-squared
Quoted Spread (bps)	140.80	86.99	0.148***	-0.114***	-7.0%	707,868	0.150
Effective Spread (bps)	4.43	3.05	0.035*	-0.157***	-10.8%	287,593	0.130
Depth (bid)	7.41	0.95	-0.059*	0.039	0.5%	707,868	0.012
Depth (L5, bid)	9.22	0.66	-0.180***	-0.019	-0.1%	707,868	0.026
Depth (ask)	7.40	0.84	-0.091***	0.217***	2.5%	707,868	0.024
Depth (L5, ask)	9.22	0.66	0.003	0.089**	0.6%	707,868	0.046
Price Impact (100ms)	2.24	3.12	0.057***	-0.187***	-26.0%	287,593	0.088
Price Impact (1 min)	3.18	4.91	0.054***	-0.033**	-5.1%	287,593	0.082
Price Impact (5 mins)	3.77	7.81	0.005	0.034**	7.0%	287,593	0.028
Messages (bid)	48.11	39.56	0.100***	-0.208***	-17.1%	707,868	0.108
PC100 (bid)	7.75	8.68	0.075***	-0.192***	-21.5%	707,868	0.044
Trade-to-order (bid)*	4.14	11.80	-0.829***	-0.058	-1.4%	529,803	0.039
Trade-to-order (ask)*	3.16	9.09	0.535***	0.321**	10.2%	545,467	0.031

Table 4 - Liquidity and Price Efficiency

The table reports our results on intraday volatility, variance ratios and Amihud liquidity from the estimation of the equation:

$$Y_{i,t} = \alpha_{P(i)} + \beta\, Drop + \gamma\, Rule201 + \xi\, Drop \times 201Rule + \varepsilon_{i,t}$$

Our sample is divided into two periods: before ($t = 0$), and after ($t = 1$) the event. Our variables of interest ($Y_{i,t}$) are $AR1\ 1min$, $VR\ Xmin$, and $Amihud\ Xmin$. $AR1\ 1min$ measures the autocorrelation of 1-minute midpoint returns for asset i, over period t. $VR\ Xmin$ is one minus the variance ratio of midpoint returns measured every X minutes relative to the 1-minute midpoint returns for asset i, over period t. $\ln Amihud\ Xmin$ measures the log of the average Amihud illiquidity ratio of absolute midpoint returns (in %) measured every X minutes relative to the volume over that same time interval for asset i, over period t. The variable $Drop$ is an indicator of the period after the event ($t = 1$), and $Rule201$ an indicator of whether i belongs to the treated group, i.e. whether the event triggers short selling constraints. The differences in sample sizes occur because we include a matched pair of assets only if it has at least 5 observations with which to compute each per period variance (at least five before, and five after the event).

Variables	Post Event	Diff-in-Diff	Constant	Observations
AR1 (1min returns)	0.00769	0.00071	0.129***	3,788
ln Amihud (1 min)	-0.361***	-0.172*	0.253***	3,780
VarR (1:5 mins)	0.042**	-0.045*	0.170***	3,751
VarR (1:10 mins)	0.006	-0.079**	0.246***	3,673

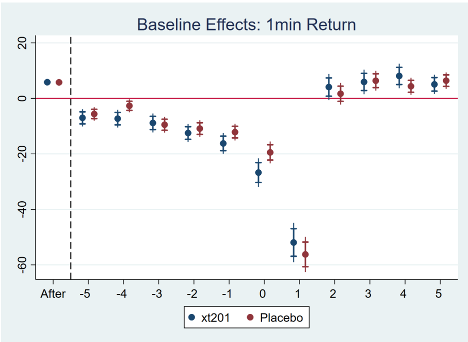
Table 5 - Further Results

The table reports the coefficients from the estimation of the model described in equation 1. All variables are standardized by the in-sample mean and standard deviation for each asset-day. * The volatility measure used is naturally comparable across assets, so it is not standardized. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

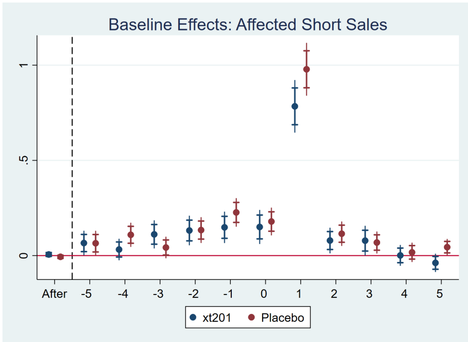
Variable	Mean	St dev	Post Event (β_1)	Diff-in-Diff (β_2)	% change	Observations	R-squared
RSpread (100 ms)	2.08	4.20	-0.013	0.062**	12.5%	287,593	0.021
RSpread (1 min)	1.11	5.41	-0.032**	-0.037**	-18.0%	287,593	0.046
RSpread (5 mins)	474.10	7.97	0.008	-0.071***	-0.1%	287,593	0.019
QuotingX	20.63	25.72	-0.008	-0.019	-2.4%	707,497	0.008
Inverted	10.64	18.96	0.001	-0.004	-0.7%	707,497	0.007
FINRA	41.28	35.36	0.033***	0.066***	5.7%	707,497	0.009
Hidden Orders	6.51	1.18	0.009*	-0.013**	-0.2%	707,868	0.003
Volatility (HL)*	0.34	0.60	0.030***	-0.032***	-9.3%	707,868	0.335

Fig. 1 - Comparisons of Coefficients.

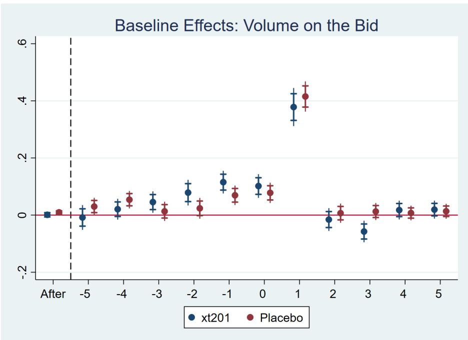
These graphs describe the differences in the coefficients between the experiment and the placebo. The coefficients are the baseline coefficients for the joint regression: $After$ is the average effect for the period after the event, and coefficient numbered $i\{-5, \ldots, 5\}$ are the coefficients for the minutes surrounding the event, $t - i$. The vertical line represents the 95 percent confidence interval. The horizontally marked intervals represent the 83 percent confidence interval, which is suggested as a visual proxy for tests of differences in mean between the coefficients, as proposed in Goldstein and Healy (1995).



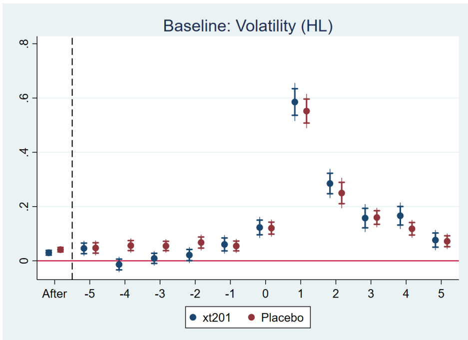
(a) One minute returns.



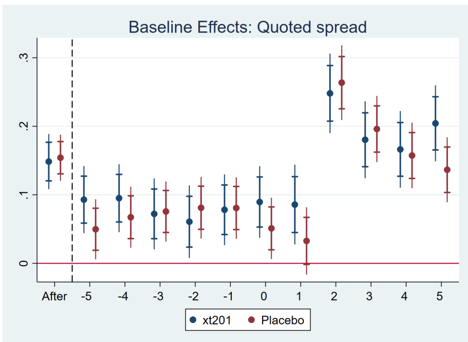
(b) Short sales at or below the bid



(c) Volume on the ask



(d) Volatility (high minus low)



(e) Quoted spread

Appendix

1. Variable Definitions

Our variables are defined as follows:

- $Market\ Capitalization$ (in logs): log of the product of the number of shares outstanding and the asset's price (source: CRSP daily).
- $Volume$ (log dollars): log of the product of the number of shares traded and the asset's price (source: CRSP daily).
- $Price$: asset's closing price.
- $Moments\ of\ daily\ returns$: *standard deviation*: standard deviation of the asset's daily returns of the past 40 trading days (source: CRSP daily).
- $Moments\ of\ daily\ returns$: *skewness*: skewness of the asset's daily returns of the past 40 trading days (source: CRSP daily)
- $Moments\ of\ daily\ returns$: *kurtosis*: kurtosis of the asset's daily returns of the past 40 trading days (source: CRSP daily)
- $Return_{i,t}$. One-minute asset return for asset i in minute t is calculated as the log difference between the midprice at the end of minute t and the beginning of minute t.
- $Range_{i,t}$. The range of price movement for asset i during minute t is calculated as the difference between the highest minus the lowest midprice during the minute, normalized by the average of the two.[23]
- $TAQVolume_{i,t}$. The (log) total dollar volume obtained by aggregating all (regular) trades in the TAQ dataset for asset i in minute t. Orders are classified as aggressive buy and sell using Lee and Ready (1991).[24]
- $\text{FINRA}^{SS}_{i,t}$. Off-exchange short selling activity for asset i in minute t measured as the log dollar total volume of the sum of trades reported as short sales to the TRF and published by FINRA on their website. Short sales are reported as $Exempt$, $Non - Exempt$, and $Total$ (the sum of the exempt and non-exempt).
- $\text{NASDAQ}^{SS}_{i,t}$. Short selling activity for asset i in minute t measured as the log dollar total volume of trades reported as short sales to the NASDAQ group exchanges. Short sales are reported as $Exempt$, $Non - Exempt$, and $Total$ (the sum of the two).
- $\text{CBOE}^{SS}_{i,t}$. Short selling activity for asset i in minute t measured as the log dollar total volume of trades reported as short sales to the BATS group exchanges. Short sales are reported as $Exempt$, $Non - Exempt$, and $Total$ (the sum of the two).
- $QuotingX$. The market share of total volume traded on the NASDAQ or NYSE exchange as reported in the TAQ dataset for asset i in minute t as a percentage of total volume.

[23] This variable is normalized in different ways in the literature. As we are working with intervals containing substantial price drops we use the arithmetic average of the two (highest and lowest) to avoid biasing the measure in any direction.
[24] For more details on the effectiveness of the Lee-Ready algorithm see Chakrabarty et al. (2012).

- $FINRA_{i,t}$. The market share of total volume traded outside official exchanges as reported in the TAQ dataset under the FINRA moniker for asset i in minute t as a percentage of total volume.
- $NASDAQVolume_{i,t}$. The (log) dollar volume obtained by aggregating trades in the ITCH dataset for asset i in minute t. Orders are separated into *visible* and *hidden* depending on whether the trade-initiating order executes against a visible (*visible*) or non-visible (*hidden*) standing order. Visible trades are classified as buy or sell orders according to the reported side of the order book of the matching limit order.
- $Quoted_{i,t}$. Quoted spread for asset i is the time-weighted (by millisecond) average, over minute t, of $(a_{t'} - b_{t'})/m_{t'}$ where $a_{t'}$ is the best ask, $b_{t'}$ the best bid, $m_{t'}$ the midprice, and t' indexes observations within a minute (source: ITCH).
- $Effective_{i,t}$. Effective spread for asset i is the intra-minute volume weighted average effective spread. The effective spread for the transaction at time t' is computed as $2\,D_{t'}(p_{t'} - m_{t'})/m_{t'}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an aggressive buy and -1 for a sale), $p_{t'}$ is the trade price and $m_{t'}$ the prevailing midquote (prior to an execution). Trade directions for visible traders are available from the ITCH dataset and do not need to be estimated. Hidden trades are classified using Lee-Ready (source: ITCH).
- $QuotedNBBO_{i,t}$. Quoted spread for asset i is the time-weighted (by millisecond) average, over minute t, of $(a_{t'} - b_{t'})/m_{t'}$ where $a_{t'}$ is the best ask, $b_{t'}$ the best bid, $m_{t'}$ the midprice, and t' indexes observations within a minute (source: TAQ).
- $Ask_{i,t}$. Depth at the Ask for asset i is calculated as the sum of the total US dollar value resting on the LOB within $X \in \{0, 5, 10\}$ cents away from the best ask, time-weighted over minute t (source: ITCH).
- $Bid_{i,t}$. Depth at the Bid for asset i is calculated as the sum of the total US dollar value resting on the LOB within $X \in \{0, 5, 10\}$ cents away from the best bid, time-weighted over minute t (source: ITCH).
- $Messages_{i,t}$. Number of messages for asset i during minute t. These include posting, canceling, and execution of visible limit orders on the corresponding side of the order book e.g. bid and ask (source: ITCH).
- $PC100_{i,t}$. Number of limit orders that are posted and subsequently canceled within 100ms for asset i during minute t (source: ITCH).
- $T2O_{i,t}$. Trade-to-order ratio computed as the number of executed visible limit orders as a percentage of messages for asset i during minute t (source: ITCH).
- $RS_{i,t}$. Realized spread for asset i is the intra-minute volume weighted average realized spread. The realized spread for the transaction at time t' is computed as $D_{t'}(p_{t'} - m_{t'+\Delta})/m_{t'+\Delta}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an aggressive buy and -1 for a sale), $p_{t'}$ is the trade price and $m_{t'+\Delta}$ the prevailing midquote at time $t + \Delta$, where Δ is a pre-specified period of time. We consider three values for Δ, namely 100ms, 1 minute, and 5 minutes. Trade directions for visible traders are available from the ITCH dataset and do not need to be estimated. Hidden trades are classified using Lee-Ready (source: ITCH).
- $PI_{i,t}$. Price Impact for asset i is the intra-minute volume weighted average price impact. The price impact for the transaction at time t' is computed as $D_{t'}(m_{t'+\Delta} - m_{t'})/m_{t'+\Delta}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an

aggressive buy and -1 for a sale), $m_{t'}$ is the prevailing midquote at time t', and $m_{t'+\Delta}$ the prevailing midquote at time $t+\Delta$, where Δ is a pre-specified period of time. We consider three values for Δ, namely 100ms, 1 minute, and 5 minutes. Trade directions for visible traders are available from the ITCH dataset and do not need to be estimated. Hidden trades are classified using Lee-Ready (source: ITCH).

- $StDev1_{i,k}$. The volatility of one-minute midprice returns over period $k \in \{0,1\}$, where $k=0$ is before the event and $k=1$ is after the event (source: ITCH).
- $AR1_{i,k}$. The auto-correlation of one-minute midprice returns $corr(r_{i,t}, r_{i,t-1})$ over period $k \in \{0,1\}$, where $k=0$ is before the event and $k=1$ is after the event (source: ITCH).
- $VR_{i,k}$ $n$min. n minute variance ratio of asset i over period $k \in \{0,1\}$, where $k=0$ is before the event and $k=1$ is after the event. The variance ratio is one minus the ratio of the sample variance of the $n-$minute returns divided by n times the sample variance of the one minute returns during period t (source: ITCH).
- $Amihud_{i,k}$ $n$min. Is the log of the average Amihud illiquidity measure for asset i over period $k \in \{0,1\}$, where $k=0$ is before the event and $k=1$ is after the event. Amihud illiquidity is measured every n minutes as the absolute return over the n minutes divided by the total dollar volume during those n minutes (source: ITCH).

2. Internet Appendix

Table A.1 - Short Selling Activity

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are different metrics of short selling activity. Data for the ALL MARKETS analysis is provided by FINRA, BATS, NYSE-ICE, and NASDAQ groups, and aggregated. In the first three columns we report results for all markets depending on how trades are marked: non-exempt, exempt and total (the sum of both). Subsequent columns use data only for the NASDAQ stock exchange. In the following four columns we separate total short-sales into passive (Passive SS NQ) and aggressive (Aggressive SS NQ) for all short-sale trades that are successfully matched with trades in the NASDAQ stock exchange. Trades are classified into buys and sells using the Lee-Ready algorithm, Lee and Ready (1991)). We separately analyze these aggressive and passive short sales based on whether they are exempt or not. In the final two columns, we separate non-exempt short sales into two groups: those at or below the national best bid (those forbidden by Rule 201, with some exceptions), and those at or above the ask (clearly passive short sales). Excluded from these two columns are non-exempt short sales with a reported price inside the NASDAQ spread, as for these the classification into aggressive buys and sells is very noisy. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

	ALL MARKETS			Passive SS NQ		Aggressive SS NQ		Non-exempt NQ	
	Non-exempt	Exempt	Total	Non-exempt	Exempt	Non-exempt	Exempt	NBB (or lower)	NBO (or higher)
Drop (β_1)	0.051***	-0.017*	0.040***	0.052***	-0.007*	0.028**	-0.011**	0.006	0.020*
T-5	0.054	0.070**	0.089***	0.042	0.029	0.064*	0.027	0.066*	0.092**
T-4	0.088***	0.046	0.085***	-0.004	0.030	0.048	0.006	0.032	0.041
T-3	0.099***	0.088***	0.100***	0.011	0.012	0.171***	0.109*	0.112**	0.176***
T-2	0.155***	0.077**	0.175***	0.075*	0.004	0.098**	0.029	0.132***	0.111**
T-1	0.272***	0.189***	0.303***	0.063*	-0.012***	0.205***	0.077	0.148***	0.215***
Event Minute (δ_0)	0.170***	0.122***	0.194***	0.015	0.036	0.120***	0.039	0.150**	0.149***
T+1	0.589***	0.471***	0.648***	0.548***	0.074*	1.046***	0.208***	0.784***	1.141***
T+2	0.204***	0.129***	0.225***	0.333***	0.001	0.262***	0.024	0.079*	0.280***
T+3	0.133***	0.093**	0.163***	0.119**	-0.001	0.078*	0.056	0.078*	0.097**
T+4	0.167***	0.092***	0.194***	0.173***	0.027	0.174***	0.037	0.001	0.176***
T+5	0.046	0.081**	0.068**	0.039	-0.005	0.078*	0.009	-0.038	0.081*
201 Rule Interactions									
Drop × 201 (β_2)	-0.132***	0.069***	-0.099***	-0.067***	0.187***	-0.264***	0.218***	-0.371***	-0.199***
T-5 interaction	0.046	0.025	0.013	0.004	-0.015	0.060	0.008	0.028	0.037
T-4 interaction	-0.031	-0.001	-0.019	0.035	-0.014	0.058	0.064*	0.040	0.092*
T-3 interaction	-0.011	-0.058	-0.022	0.005	-0.010	-0.099	-0.082	-0.073	-0.097
T-2 interaction	-0.087*	-0.009	-0.082*	-0.060	0.056	-0.007	0.024	0.040	-0.019
T-1 interaction	-0.128***	-0.089*	-0.150***	-0.031	0.046**	-0.022	-0.028	0.028	-0.028
Event Minute × 201 (η_0)	0.015	-0.070	0.003	-0.017	-0.020	0.094	0.008	0.102	0.042
T+1 interaction	0.040	-0.120*	0.023	-0.008	0.041	0.169	0.237**	0.213*	0.138
T+2 interaction	0.067	-0.078	0.050	-0.110	0.080	0.054	0.096	0.038	0.039
T+3 interaction	0.126***	-0.061	0.094*	-0.025	0.053	0.160**	0.099	-0.020	0.159**
T+4 interaction	-0.006	-0.061	-0.024	-0.082	0.062	-0.019	0.053	0.054	-0.021
T+5 interaction	0.143***	-0.055	0.129***	0.069	0.046	0.062	0.001	0.138***	0.043
Observations	709,352	709,352	709,352	707,868	707,868	707,868	707,868	707,868	707,868
R-squared	0.029	0.016	0.034	0.017	0.013	0.053	0.013	0.056	0.056
# Events	1,908	1,908	1,908	1,908	1,908	1,908	1,908	1,908	1,908

Table A.2 - TAQ Volumes

The table reports the coefficients from the estimation of the model described in equation 1. The table reports our results on trading activity defined as the record of transactions in the Trade and Quote (TAQ) Database. Our variables of interest ($Y_{i,t}$) are the (log) total dollar volume obtained by aggregating all (regular) trades in the TAQ dataset for asset i in minute t. *AggB* (*Ask*) reports the results considering orders classified as aggressive buy orders (Buyer Initiated Transactions). *AggS* (*Bid*) reports the results considering only aggressive sell orders (Seller Initiated Transactions) and *Total* reports the results for the total number of transactions, regardless of their type. Orders are classified as aggressive buy and sell using Lee and Ready (1991). All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

LOG VOLUME (All markets)	AggS (Bid)	AggB (Ask)	Total
Drop (β_1)	-0.016	0.092***	0.035**
T-5	0.231***	0.180***	0.243***
T-4	0.191***	0.069*	0.187***
T-3	0.200***	0.128***	0.226***
T-2	0.248***	0.157***	0.246***
T-1	0.326***	0.258***	0.315***
Event Minute (δ_0)	0.435***	0.272***	0.413***
T+1	1.225***	0.818***	1.083***
T+2	0.462***	0.363***	0.453***
T+3	0.240***	0.227***	0.292***
T+4	0.246***	0.346***	0.334***
T+5	0.140***	0.259***	0.233***
201 Rule Interactions			
Drop × 201 (β_2)	-0.094***	-0.043**	-0.076***
T-5 interaction	-0.075	-0.044	-0.089*
T-4 interaction	0.009	0.016	0.008
T-3 interaction	0.006	0.022	-0.014
T-2 interaction	-0.014	-0.015	-0.046
T-1 interaction	-0.044	-0.050	-0.038
Event Minute × 201 (η_0)	-0.080	-0.003	-0.067
T+1 interaction	0.012	0.081	0.013
T+2 interaction	-0.021	0.001	-0.002
T+3 interaction	0.158***	0.039	0.089
T+4 interaction	-0.021	-0.098*	-0.081
T+5 interaction	0.040	-0.121*	-0.057
Observations	707,497	707,497	707,497
R-squared	0.080	0.051	0.079
# Events	1,907	1,907	1,907

Table A.3 - Returns and Volatilities

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are Returns and Range (Volatility). *Return* (*bps*) reports the results for stock returns, where $Y_{i,t}$ is $Return_{i,t}$, defined as the asset one-minute return for asset i in minute t and is calculated as the log difference between the midprice at the end of minute t and the beginning of minute t. *Range* reports the results for our measure of volatility, where $Y_{i,t}$ is $Range_{i,t}$, calculated as the difference between the highest minus the lowest midprice during the minute, normalized by the average of the two. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

STOCK PRICE: VOLATILITY & RETURN	Return (bps)	Range
Drop (β_1)	5.821***	0.030***
T-5	-7.020***	0.046**
T-4	-7.307***	-0.014
T-3	-8.862***	0.009
T-2	-12.484***	0.021
T-1	-16.224***	0.060***
Event Minute (δ_0)	-26.730***	0.123***
T+1	-51.930***	0.585***
T+2	4.081	0.285***
T+3	5.918**	0.157***
T+4	8.069***	0.166***
T+5	5.047**	0.076***
201 Rule Interactions		
Drop × 201 (β_2)	0.734***	-0.353***
T-5 interaction	-0.174	-0.014
T-4 interaction	3.034	0.044*
T-3 interaction	-0.719	0.019
T-2 interaction	3.172	0.005
T-1 interaction	1.280	-0.008
Event Minute × 201 (η_0)	-2.130	-0.016
T+1 interaction	-2.992	0.030
T+2 interaction	3.636	-0.017
T+3 interaction	0.300	0.043
T+4 interaction	-2.065	-0.020
T+5 interaction	2.906	0.004
Observations	707,868	707,868
R-squared	0.009	0.335
# Events	1,908	1,908

Table A.4 - NASDAQ Volume (Visible vs. Hidden)

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the (log) dollar volume in the NASDAQ market obtained by aggregating trades in the ITCH dataset for asset i in minute t. Orders are separated into *visible* and *hidden* depending on whether the trade-initiating order executes against a visible (*visible*) or non-visible (*hidden*) standing order. Visible trades are classified as buy or sell orders according to the reported side of the order book of the matching limit order. *AggB* (*Ask*) reports the results considering only orders classified as aggressive buy orders (Buyer Initiated Transactions). *AggS* (*Bid*) reports the results considering only aggressive sell orders (Seller Initiated Transactions) and $Total$ reports the results for the total number of transactions, regardless of their type. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

VOLUME	Visible AggS (Bid)	Visible AggB (Ask)	Visible Total	Hidden Total
Drop (β_1)	0.001	0.018***	0.019**	0.009*
T-5	-0.008	0.037*	0.038	0.024*
T-4	0.021	0.037*	0.042	-0.013
T-3	0.046*	0.012	0.040	-0.014
T-2	0.079***	0.051**	0.097***	0.045**
T-1	0.115***	0.054**	0.140***	0.024
Event Minute (δ_0)	0.102***	0.040*	0.137***	0.006
T+1	0.378***	0.179***	0.498***	0.139***
T+2	-0.016	0.088***	0.079**	0.028
T+3	-0.057**	0.065***	0.009	0.007
T+4	0.018	0.052**	0.065**	-0.004
T+5	0.019	-0.001	0.005	-0.023
201 Rule Interactions				
Drop × 201 (β_2)	-0.031***	-0.011*	-0.043***	-0.013**
T-5 interaction	0.016	-0.001	-0.006	-0.003
T-4 interaction	-0.016	-0.008	-0.004	0.007
T-3 interaction	-0.003	-0.001	0.008	0.028
T-2 interaction	-0.020	-0.056*	-0.042	-0.060**
T-1 interaction	-0.048	-0.031	-0.057	0.010
Event Minute × 201 (η_0)	0.000	-0.007	-0.013	0.056*
T+1 interaction	0.070	0.007	0.071	-0.002
T+2 interaction	0.034	-0.014	0.031	0.005
T+3 interaction	0.062*	-0.002	0.055	0.004
T+4 interaction	-0.033	-0.006	-0.026	0.022
T+5 interaction	-0.039	0.027	0.013	0.056**
Observations	707,868	707,868	707,868	707,868
R-squared	0.021	0.013	0.014	0.003
# Events	1,908	1,908	1,908	1,908

Table A.5 - Effective and Quoted Spreads

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are $QSp_{i,t}$, $EffSp_{i,t}$ and $QSp_{NBBO,i,t}$. $QSp_{i,t}$ is the time-weighted quoted spread calculated with ITCH database (NASDAQ). $EffSp_{i,t}$ is the volume-weighted effective spread calculated with ITCH database (NASDAQ). $QSp_{NBBO,i,t}$ is the time-weighted quoted spread calculated with the NBBO of the TAQ database. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

SPREADS	Quoted	Effective	Quoted NBBO
Drop (β_1)	0.148***	0.035*	0.194***
T-5	0.093***	0.036	0.118***
T-4	0.095***	0.053	0.107***
T-3	0.072**	-0.059	0.104***
T-2	0.061*	0.013	0.106***
T-1	0.078**	-0.024	0.088**
Event Minute (δ_0)	0.089***	0.015	0.134***
T+1	0.086**	0.288***	0.106***
T+2	0.248***	0.204***	0.267***
T+3	0.180***	0.230***	0.219***
T+4	0.166***	0.200***	0.145***
T+5	0.204***	0.098*	0.161***
201 Rule Interactions			
Drop × 201 (β_2)	-0.114***	-0.157***	-0.146***
T-5 interaction	-0.044	-0.023	-0.011
T-4 interaction	-0.043	-0.036	0.016
T-3 interaction	-0.030	-0.001	0.004
T-2 interaction	-0.048	-0.002	-0.008
T-1 interaction	-0.046	0.031	0.040
Event Minute × 201 (η_0)	-0.067	0.010	0.011
T+1 interaction	0.050	0.056	0.086
T+2 interaction	0.099*	0.131*	0.091
T+3 interaction	0.128**	-0.026	0.087
T+4 interaction	0.119**	0.006	0.122*
T+5 interaction	0.061	0.007	0.108*
Observations	707,868	287,593	704,751
R-squared	0.150	0.130	0.109
# Events	1,908	1,908	1,907

Table A.6 - Depth

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the LOB depth $DX_{i,t}$, calculated as the sum of the total US dollar value resting on the LOB within $X \in \{0, 5, 10\}$ cents away from the best bid and ask, for asset i and time-weighted over minute t. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

DEPTH	Bid	Bid-5c	Bid-10c	Ask	Ask+5c	Ask+10c
Drop (β_1)	-0.059*	-0.180***	-0.213***	-0.091***	0.003	0.016
T-5	0.145***	0.042	0.050	0.086**	0.091**	0.077*
T-4	0.132***	0.035	0.048	0.065	0.082*	0.069*
T-3	0.083*	0.047	0.040	0.115***	0.107**	0.080*
T-2	0.084*	0.003	0.034	0.143***	0.078*	0.062
T-1	0.082*	0.013	0.040	0.159***	0.065	0.045
Event Minute (δ_0)	0.092*	0.067	0.041	0.164***	0.042	0.003
T+1	0.247***	0.261***	0.228***	0.211***	0.010	-0.034
T+2	0.082*	0.142***	0.082*	0.082*	-0.045	-0.047
T+3	0.067*	0.116**	0.053	0.020	-0.043	-0.083*
T+4	0.050	0.094**	0.058	-0.005	-0.041	-0.113**
T+5	0.038	0.091*	0.055	0.001	-0.088**	-0.123***
201 Rule Interactions						
Drop × 201 (β_2) interaction	0.039	-0.019	-0.047	0.217***	0.089**	0.041
T-5 interaction	-0.097*	0.024	-0.061	-0.031	-0.067	-0.075
T-4 interaction	-0.098	0.039	-0.047	-0.038	-0.087*	-0.097*
T-3 interaction	-0.025	0.025	-0.047	-0.066	-0.114*	-0.106*
T-2 interaction	-0.060	0.033	-0.043	-0.074	-0.048	-0.068
T-1 interaction	-0.021	0.036	-0.056	-0.054	-0.035	-0.075
Event Minute × 201 (η_0)	-0.017	-0.041	-0.094	-0.020	-0.019	-0.046
T+1 interaction	-0.065	-0.055	-0.072	-0.239***	-0.125**	-0.112*
T+2 interaction	-0.055	-0.089	-0.059	-0.144**	-0.141**	-0.136**
T+3 interaction	-0.032	-0.087	-0.051	-0.078	-0.121**	-0.086
T+4 interaction	-0.055	-0.056	-0.047	-0.029	-0.096*	-0.044
T+5 interaction	-0.041	-0.085	-0.049	-0.056	-0.055	-0.038
Observations	707,868	707,868	707,868	707,868	707,868	707,868
R-squared	0.012	0.026	0.024	0.024	0.046	0.029
# Events	1,908	1,908	1,908	1,908	1,908	1,908

Table A.7 - Price Impact

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the intra-minute volume weighted average price impact for asset i, $PI_{i,t}$. The price impact for the transaction at time $t' \in [t, t+1)$ is computed as $D_{t'}(m_{t'+\Delta} - m_{t'})/m_{t'+\Delta}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an aggressive buy and -1 for a sale), $m_{t'}$ is the prevailing midquote at time t', and $m_{t'+\Delta}$ the prevailing midquote at time $t+\Delta$, where Δ is a pre-specified period of time. We consider three values for Δ, namely 100ms, 1 minute, and 5 minutes. Trade directions for visible trades are available from the ITCH dataset. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

PRICE IMPACT	100ms	1min	5min
Drop (β_1)	0.057***	0.054***	0.005
T-5	0.040	0.019	0.151*
T-4	-0.059	0.017	0.347***
T-3	-0.082*	0.007	0.575***
T-2	-0.046	-0.033	0.342***
T-1	0.015	0.357***	0.315***
Event Minute (δ_0)	0.127**	0.522***	0.140**
T+1	0.051	-0.010	-0.149***
T+2	-0.033	0.038	0.099*
T+3	0.160***	0.135**	0.187***
T+4	0.088*	0.097*	0.116*
T+5	0.007	-0.027	-0.039
201 Rule Interactions			
Drop × 201 (β_2)	-0.187***	-0.033**	0.034**
T-5 interaction	-0.133*	-0.037	0.073
T-4 interaction	0.099	0.134*	0.054
T-3 interaction	0.046	-0.010	-0.163
T-2 interaction	-0.015	0.148*	-0.014
T-1 interaction	-0.076	-0.245***	-0.097
Event Minute × 201 (η_0)	-0.251***	-0.017	-0.033
T+1 interaction	0.148**	0.027	-0.048
T+2 interaction	0.213***	0.051	-0.007
T+3 interaction	0.043	0.013	-0.142
T+4 interaction	0.040	-0.020	-0.027
T+5 interaction	0.090	0.057	0.049
Observations	287,593	287,593	287,593
R-squared	0.088	0.082	0.028
# Events	1,908	1,908	1,908

Table A.8 - Algorithmic Activity

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are $Messages_{i,t}$ $PC100_{i,t}$ and $T2O_{i,t}$. $Messages_{i,t}$ is the number of messages for asset i during minute t including posting, cancelling, and execution of visible limit orders on the corresponding side of the order book (bid and ask). $PC100_{i,t}$ is number of limit orders that are posted and subsequently cancelled within 100ms for asset i during minute t. $T2O_{i,t}$ is the trade-to-order ratio computed as the number of executed visible limit orders as a percentage of messages for asset i during minute t. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

ALGORITHM ACTIVITY	Messages (Bid)	Messages (Ask)	PC100 (Bid)	PC100 (Ask)	T2O (Bid)	T2O (Ask)
Drop (β_1)	0.100***	0.007	0.075***	0.010	-0.829***	0.535***
T-5	0.151***	0.242***	0.106**	0.083**	0.176	-0.464*
T-4	0.025	0.103**	0.014	0.015	0.876	-0.608**
T-3	0.067*	0.202***	0.010	0.050	1.383**	-1.074***
T-2	0.145***	0.252***	0.088*	0.132***	0.488	-0.424*
T-1	0.276***	0.392***	0.139***	0.256***	1.346**	-0.043
Event Minute (δ_0)	0.374***	0.589***	0.200***	0.291***	0.418	-0.798***
T+1	1.670***	1.908***	1.066***	1.460***	6.873***	0.517*
T+2	0.510***	0.641***	0.392***	0.331***	0.055	-0.342
T+3	0.249***	0.359***	0.182***	0.195***	0.338	-0.290
T+4	0.218***	0.271***	0.242***	0.154***	-0.410	0.457
T+5	0.091**	0.143***	0.058	-0.004	-0.500	0.306
201 Rule Interactions						
Drop × 201 (β_2)	-0.208***	-0.105***	-0.192***	-0.131***	-0.058	0.321**
T-5 interaction	-0.121**	-0.164***	-0.137**	-0.048	0.166	0.608
T-4 interaction	0.043	0.056	-0.001	0.034	-0.188	0.100
T-3 interaction	0.005	-0.008	0.008	0.019	-0.376	0.893***
T-2 interaction	-0.056	-0.047	-0.089	-0.043	0.690	-0.276
T-1 interaction	-0.070	-0.107	-0.064	-0.150**	-0.663	-0.187
Event Minute × 201 (η_0)	-0.017	-0.108	-0.119*	-0.129*	0.106	0.053
T+1 interaction	0.060	0.067	0.192	0.074	-1.913*	-0.256
T+2 interaction	-0.089	-0.136*	-0.107	-0.059	-0.263	0.233
T+3 interaction	0.001	-0.079	-0.014	-0.005	-0.283	0.065
T+4 interaction	-0.015	-0.047	-0.112*	0.010	0.117	-0.710
T+5 interaction	0.049	0.010	0.026	0.129**	0.878	-0.688
Observations	707,868	707,868	707,868	707,868	529,803	545,467
R-squared	0.108	0.162	0.044	0.091	0.039	0.031
# Events	1,908	1,908	1,908	1,908	1,908	1,903

Table A.9 - Realized Spreads

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the intra-minute volume weighted average realized spread $RS_{i,t}$. The realized spread for the transaction at time $t' \in [t, t+1)$ is computed as $D_{t'}(p_{t'} - m_{t'+\Delta})/m_{t'+\Delta}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an aggressive buy and -1 for a sale), $p_{t'}$ is the trade price and $m_{t'+\Delta}$ the prevailing midquote at time $t+\Delta$, where Δ is a pre-specified period of time. We consider three values for Δ, namely 100ms, 1 minute, and 5 minutes. Trade directions for visible trades are available from the ITCH dataset. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

REALIZED SPREAD	100ms	1min	5min
Drop (β_1)	-0.013	-0.032**	0.008
T-5	0.014	-0.001	-0.158*
T-4	0.073	0.008	-0.392***
T-3	0.106*	-0.031	-0.641***
T-2	0.074	0.057	-0.339***
T-1	-0.001	-0.376***	-0.356***
Event Minute (δ_0)	-0.109*	-0.523***	-0.150**
T+1	0.146***	0.145***	0.239***
T+2	0.174***	0.039	-0.072
T+3	-0.021	-0.049	-0.145**
T+4	0.031	-0.009	-0.070
T+5	0.061	0.069	0.066
201 Rule Interactions			
Drop × 201 (β_2)	0.062**	-0.037**	-0.071***
T-5 interaction	0.104	0.033	-0.070
T-4 interaction	-0.099	-0.159*	-0.041
T-3 interaction	-0.116*	0.021	0.172
T-2 interaction	-0.001	-0.167*	-0.012
T-1 interaction	0.052	0.252***	0.114
Event Minute × 201 (η_0)	0.241***	-0.058	0.035
T+1 interaction	-0.110*	-0.020	0.054
T+2 interaction	-0.085	0.007	0.050
T+3 interaction	-0.031	-0.016	0.134
T+4 interaction	-0.042	0.017	0.018
T+5 interaction	-0.082	-0.069	-0.067
Observations	287,593	287,593	287,593
R-squared	0.021	0.046	0.019
# Events	1,908	1,908	1,908

Table A.10 - Share Volumes

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are standardized transacted share volume provided by FINRA and TAQ classified into three groups $QuotingX_{i,t}$, $FINRA_{i,t}$ and $Inverted_{i,t}$. $QuotingX_{i,t}$ stands for the market share of total volume traded on the asset's quoting exchange (CRSP), obtained from the TAQ dataset for asset i in minute t as a percentage of total volume. $FINRA_{i,t}$ stands for the market share of total volume traded outside official exchanges as reported in the TAQ dataset under the FINRA moniker for asset i in minute t as a percentage of total volume. $Inverted_{i,t}$ stands for the market share of total volume traded on the markets with inverted fee structure. $AggB$ (Ask) reports the results considering only orders classified as aggressive buy orders (Buyer Initiated Transactions). $AggS$ (Bid) reports the results considering only aggressive sell orders (Seller Initiated Transactions) and $Total$ reports the results for the total number of transactions, regardless of their type. Orders are classified as aggressive buy and sell using Lee and Ready (1991). All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

MARKET SHARE	QuotingX AggS (Bid)	QuotingX AggB (Ask)	QuotingX Total	FINRA AggS (Bid)	FINRA AggB (Ask)	FINRA Total	Inverted AggS (Bid)	Inverted AggB (Ask)	Inverted Total
Drop (β_1)	0.009	-0.005	-0.008	-0.004	0.023**	0.033***	-0.004	0.006	0.001
T-5	-0.070**	0.001	-0.036	0.074**	0.032	0.075**	-0.031	-0.042	-0.083***
T-4	-0.033	-0.052*	-0.048	0.095***	0.065*	0.097**	-0.060*	-0.012	-0.064*
T-3	-0.053*	-0.020	-0.062*	0.111***	0.063*	0.114***	-0.025	-0.070***	-0.061*
T-2	-0.069**	-0.074**	-0.062*	0.065**	0.063*	0.073**	-0.033	-0.005	-0.038
T-1	-0.040	-0.013	-0.049	0.028	0.037	0.040	-0.055**	-0.007	-0.029
Event Minute (δ_0)	-0.073**	-0.061*	-0.100***	0.097***	0.118***	0.146***	-0.048	-0.066**	-0.040
T+1	0.025	0.220***	0.212***	-0.037	-0.118***	-0.136***	-0.114***	-0.037	-0.097***
T+2	0.018	-0.011	-0.008	0.040	0.107***	0.073*	-0.048	-0.062**	-0.051
T+3	-0.025	-0.028	-0.068**	0.073**	0.029	0.063*	-0.063**	-0.053**	-0.069**
T+4	-0.022	-0.037	-0.049	0.039	0.056*	0.066*	-0.056*	-0.034	-0.081***
T+5	-0.017	-0.029	-0.034	0.049	0.017	0.050	-0.046	-0.061**	-0.060*
201 Rule Interactions									
Drop × 201 (β_2)	-0.028**	-0.024*	-0.019	0.033***	0.079***	0.066***	-0.035***	0.025**	-0.004
T-5 interaction	0.021	-0.013	-0.014	0.030	0.005	0.024	0.010	0.034	0.049
T-4 interaction	0.004	0.098**	0.073	-0.064	-0.041	-0.060	0.004	0.031	0.031
T-3 interaction	0.044	-0.007	0.031	-0.076*	-0.021	-0.056	-0.029	0.052	0.011
T-2 interaction	0.030	0.056	0.014	0.007	0.006	0.034	0.006	-0.002	0.024
T-1 interaction	0.072*	-0.019	0.024	0.011	0.027	0.050	-0.010	-0.033	-0.052
Event Minute × 201 (η_0)	0.015	0.102**	0.109**	-0.024	-0.098**	-0.107**	-0.015	0.035	-0.012
T+1 interaction	0.162***	0.075	0.119**	-0.083*	-0.089**	-0.083*	0.022	-0.076*	-0.034
T+2 interaction	0.027	0.039	0.045	0.004	-0.081*	-0.034	-0.005	0.041	0.014
T+3 interaction	0.050	0.073	0.096*	0.003	-0.020	0.013	0.025	-0.008	-0.006
T+4 interaction	0.035	0.017	0.058	0.008	-0.053	-0.018	0.017	0.014	0.021
T+5 interaction	-0.007	0.097**	0.056	-0.015	-0.083*	-0.057	-0.025	0.035	-0.018
Observations	707,497	707,497	707,497	707,497	707,497	707,497	707,497	707,497	707,497
R-squared	0.002	0.012	0.008	0.002	0.012	0.009	0.003	0.008	0.007
# Events	1,907	1,907	1,907	1,907	1,907	1,907	1,907	1,907	1,907